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EXAMINATION OF BASIC DATA MEASUREMENT SCALES AND STATISTICAL TECHNIQUES TESTS RELEVANCE IN CONTEMPORARY BUSINESS MANAGEMENT RESEARCH: A DISCOURSE

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ABSTRACT

The knowledge of the specific scale of data measurement and selection of the appropriate statistical techniques test is the most difficult, yet the most important of the research process and statistical decision making. This study empirically examined the four basic measure scales of data measurement, the basic statistical tests and the highlight of the purposes and types of data required for each managerial decision making in the basic statistical test of significance. Their relative computational examples of practical relevance in contemporary business management research and management were also highlighted. The basic data measurements scales considered are: nominal, ordinal, interval and ratio, while the basic statistical test of significance tools examined include: the Chi-square test, the Student t-test, the Z-score test, the Pearson Product Moment Correlation; the Spearman's Rank Order Correlation; the Simple Regressional Analysis, as well as the Analysis of Variance (ANOVA). In each of the cases, the study examined the type of data appropriate for the chosen scale of measurement and techniques. Relevant hypotheses relating to each case were also posited and analysis was done for management guides and decisions. The description of these basic scales and statistical techniques tests and their importance when considering and choosing how to go about measuring the variables that may be considered in the research study were also discussed and conclusions made. Appropriate scale usage and analytical techniques were also recommended.

KEYWORDS: Data Examination, Measurement Scales, Statistical Relevance, Decision Making & Statistical Test Techniques

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1. INTRODUCTION

The phrase "scale of measurement" usually refers to the units in which a variable is measured. However, this phrase can also refer to the type of scale represented by a given set of units. A scale may be looked upon as any measuring instrument (questionnaire, interview, test, observation, etc.) composed of one or more 'items" (question, observation, etc.) that have logical or empirical relationships with one another (Selitiz, Wrightsman, and Cook, 1976). That is, a scale may be looked upon as a set of "items" constructed which may constitute entities (people, things, events, etc.) being measured (i. e. scaled) and can be systematically assigned scores on the scale, the assignment of such scores being related to the "amount" of the measured attribute the entity possesses (Kerlinger, 1973). Stevens (1968, in Stone, 1978) noted that scales are created by the formulation of rules for assigning numerals or symbols to aspects (i. e. attributes) of objects or event.

Stevens (1946, in Bordens and Abbott, 2002) identified four basic scales, which can be arranged in order of increasing information provided about the values along the scale. Stevens expressed that while hundreds of thousands of scales probably exist for measuring the various attributes of people, things, objects, events, etc.; all scales can be assigned to one or four basic types in order of increasing information provided about the values along the scale, viz: nominal, ordinal, intervals, and ratio scales.

Having made the brief expression of what a scale of measurement and scale itself are, we have hereunder described these basic scales and discussed why they are important to consider when choosing how to go about measuring the variables we may consider in our study.

1.1 Nominal Scale

Nominal scale is the most fundamental in descriptive research. As the term implies, nominal means names. That is, observations are classified into categories with no necessary relation existing between the categories. In applying such a scale, an individual is assigned to the appropriate category according to the definition of the category. At the lowest level of measurement, a variable may simply define a set of cases or types. For example, sex may be male or female. According to one scheme, a person’s personality may be classified as introverted or extroverted, variables whose values differ by category are said to fall along a nominal scale. The scale is qualitative in nature. In the nominal scale, the values have different names, but no ordering of the values is implied. For example, to say that male is higher or lower than female in nominal scale makes no sense. They are simply different. It also makes no sense to multiply, divide, add, or subtract nominal values, (Bordens and Abbott, 2002).

1.2 Ordinal Scale

At the next level of measurement are variables measured along an ordinal scale. The different values of a variable in an ordinal scale not only have different names (as in the nominal scale) but also can be ranked according to quantity. The ordinal scale is a rank ordering of things. The ranking may be according to some underlying continuum of intensity or severity, as in most severe to the least severe i. e. range. For example, in ordinal scaling, objects, persons, events, etc., are ranked (least to most, smallest to largest, low to high, etc.) with respect to the measured attribute.

It should therefore, be apparent and noted, therefore, that while ordinal scaling tells us how things are ranked with respect to some measured attributes, we know nothing about the distances between the ranked items on the measured attribute. All we can say for sure is that moderate is greater than low and high is greater than moderate. Quantification of data collected with ordinal scales is similar to that employed in the use of nominal scales. An ordinal scale is also qualitative in nature, just as is in nominal scale.

1.3 Interval Scale

In the case of interval scales, objects are not only ordered with respect to some measured attribute, but the intervals between adjacent points on the measurement are equal. It is possible to determine distances among objects with respect to the measured attribute. Interval scales, therefore, use predetermined equal intervals. They tell the interval or distance between judgements. It is to be noted that on an interval scale, a distance of so many points may therefore, be considered a relative constant at any point on the scale where it occurs. Also, in an interval scale, responses may be recorded on a five-point scale with the following anchors: very little extent; some extent; considerable extent; the great extent and very great extent.

1.4 Ratio Scale

Ratio scales have all the properties of interval scales. In addition, a logical or absolute zero point for the scale exists. This scale is seldom used in administrative sciences measures because the scale includes a true zero value. That is, a point on the scale that represents complete absence of the characteristic involved, and ratios are comparable at different points on the scale (Tuckman, 1978; in Baridam, 1990). Measures such as for length, weight, and many other physical measures have ratio scale properties. The result of any counting operation also results in ratio scaling, since there may be 0, 1, 2, 3, …, or N objects.

2. SCALE OF MEASURE, PURPOSE AND TYPE OF DATA REQUIRED FOR STATISTICAL TEST OF SIGNIFICANCE

2.1 Chi-square statistic (X^2) Test (Uses Nominal Scale)

The Chi-square for contingency tables (also called the Chi-square test for independence) is a non-parametric statistical test designed for frequency data in which the difference or contingency between two variables are to be determined. When our dependent variable is a dichotomous decision (such as yes-no or agree-disagree situations or a frequency count of events and sets of people or departmental productivity, the test statistic choice is Chi-square (X^2). The type of data and scale of measure required in Chi-square statistical test of significance in, particular, is nominal scale. Chi-square is a test of difference and is one of the most widely used tests based on notions of probability, and frequency data set into contingency table, arranged in horizontal rows and vertical columns depending on the number of variables in each case.

For example, in an income level and academic production achievement preference study, one may measure the income level of the respondent in addition to candidate's productivity achievement preference. One may want to know whether there is a significant difference between the two variables or independent. The Chi-square test for contingency tables compares the observed cell frequencies (i. e. those one obtained in the study) with expected cell frequencies (i. e. those one would expect to find if chance alone were operating).

The chi-square test is used to measure the difference between a statistically generated expected result and an actual result to see if there is a statistically significant difference between them (Cohens Manion, and Morrison, 2007). This implies to verify if the frequencies observed are significant. Chi-square is noted to be a measure of 'goodness of fit' between an expected and an actual result or set of results.

2.1.1 Limitations of Chi-Square

A problem arises if any of the expected cell frequencies are less than five. In such cases, the value of chi-square may be artificially inflated (Gravetter and Wallnau, 2000) i. e. x^2 will be overestimated and such will lead to the commission of type 1 error-i. e. rejection of the null hypothesis. It is also noted that under such a situation, three options are suggested to deal with the problem.

First, one could include more subjects to increase the sample size. Second, one could also combine cells (if it is logical to do so). For example, one could categorize subjects into three categories rather than five (i. e. the particular category may be merged with the next lower or next higher category). Third, one could consider a different test. The Fisher exact probability test also uses nominal scale test (as in chi-square) and this is an alternative to chi-square (Roscoe, 1975;

Siegel and Castellan, 1988), when one has small expected frequencies and a 2x2 contingency table. A significant chi-square tells us that our two variables are significantly related.

However, chi-square does not tell us where the significant differences occur when more than two categories of each variable exist. To determine the locus of the significant effects, it is suggested that one can conduct separate chi-square tests on specific cells of the contingency table (Bordens and Abbott, 2002).

2.1.2 Use of Chi-square and its Nominal Scale Data as a Computational example of Practical Relevance in Management Sciences

2.1.2.1 Example (Baridam, 1990)

For illustration purpose, suppose a researcher is interested in finding if there is any significant difference between the production achievement of a Social Science Academic Staff and their income level in a University. The researcher's null hypothesis is that there is no significant difference between the Journal articles production achievement of SocialScience Academic Staff and their level of income; while the alternative hypothesis is that there is a significant difference. For this test, let us assume that the researcher selects 0.05 level of significance.

It is to be noted that the researcher classifies Journal articles production achievement of Social Science Academic Staff into three groups as relatedly argued by Baridam (1990): (a) above average; (b) average; (e) and below average. Let us also assume according to Baridam (1990) in table 1 below, that his sample is 745 staff and that these respondents are classified into four income levels: Upper; Upper middle, Lower middle and Lower. The respondents of the 745 staff are represented in Table 1. This is a 3 x 4 contingency table.

Table 1: Production Achievement and Income Level

Journal articles Production Achievement	Income Level				Total
	Upper	Upper middle	Lower Middle	Lower	
Above average	7(5)	33(29)	35(35)	20(26)	95
Average	15(27)	70(71)	90(87)	60(65)	235
Below average	18(22)	122(125)	150(153)	125(114)	415
Total	**40**	**225**	**275**	**205**	**745**

Source: Baridam, D. M. (1990). *Research Methods in Administrative Sciences,* Port Harcourt: BELK Publishers (with modifications)

$$\chi^2 = \frac{\sum(fo - fe)}{fe}$$

fe = expected frequency

fo = actual or observed frequency

Note: Figures in brackets in the table are expected frequencies

Based on the data in Table 1 above, 95 out of 745 staff have an above average productivity achievement (Baridam, 1990). If we assume that no significant difference exists between Journal articles production achievement and income level, the expectation will be that 40 staff who had upper income would have 15 average production records. As a result, the expected frequency for that cell would be 27. Further, if there is no significant difference between production achievement and income level, the expectation is that 225 staff who belong to the upper-middle-income level would also

have an above- average of 33. The expected frequency (fe) as specified for that cell is 29. This procedure should be continued untill the expected frequency for each cell is calculated.

In order to determine the level of significance of the computed value of Chi-square, we refer to the distribution of Chi-square values. This distribution can be found in table form in most statistical texts appendices. We can also determine the number of degrees of freedom (df) associated with the observed data in the contingency table.

This accordingly is given as:

d. f (R-1) (C-1)

Where R = number of rows

C = number of columns.

In this case, the d. f = (3-1) (4-1) =6; i. e. 2x3

The critical value of 6 degrees of freedom and an alpha or level of significance of 0.05 is 12.59.

The null hypothesis (H_o), conventionally will be accepted if the computed value of χ^2 is less than 12.59. Otherwise, H_o will be rejected and the alternative hypothesis (H_A) will be accepted.

In the example above, the computed χ^2 as derived from the formula is 6.3. This computed value is therefore, less than the critical (tabulated) value (12.59), and this falls in the acceptance region. The null hypothesis which states that there is no significant difference between academic production achievement and income level in the study area is accepted at the 5 percent level of significance.

2.2 Student t-test (i. e. the t-test)

This statistical test is a parametric test for samples (less than 30) based on student t distribution. It tests the difference between only two numbers which are gotten from summary measures of continuous variables. The test uses the interval scale of measurement.

As opined by Osaat and Nwanna-Nzewunwa (2002), there are three basic types of tests such as:

- The t-test for correlated groups;
- The t-test for correlated independent groups; and
- The t-tests for small independent groups.

2.2.1 The t-tests for Correlated Groups

This is applied when the means of two distributions to be compared come from the same sample. For example, Management Sciences students mean scores in Marketing and Accounting courses in the specific subject area can be compared by using this test, that is the same set of students;

The formula is:

$$t = \frac{\overline{D}}{\sqrt{\frac{N\sum D^2 - (D)}{N^2 (N-1}}}$$

Where: D =Differences between the paired

$\overline{D}$ = The means of the difference

N-1 =Degrees of freedom

N = The number of pairs

$\sum D^2$ = The sum of the squared difference scores

Table 2: Ten Management Sciences Students Scores in Marketing and Accounting

Student	Marketing	Accounting	Marketing-Accounting	D^2
1	30	20	-10	100
2	50	60	-10	100
3	40	45	-5	25
4	55	50	-5	25
5	62	70	-8	64
6	25	30	-5	25
7	35	32	3	9
8	40	35	5	25
9	65	50	15	225
10	60	65	-1	25
			$\sum 5$	$\sum \mathbf{D^2 = 623}$

From the above table,

$\sum D = 5$

$$\overline{D} = \frac{\sum D}{10} = \frac{5}{10} = 0.5$$

$\sum D^2 = 625$

From the formula,

$$t = \frac{0.5}{\frac{\sqrt{(10\,x 62.3) - 5^2}}{10^2(10-1)}} = \frac{0.5}{\frac{\sqrt{(6230) - 25}}{100\,x 9}} = \frac{0.5}{\frac{\sqrt{62058}}{900}}$$

$$\Rightarrow t = \frac{0.5}{\sqrt{6.894444444}} = \frac{0.5}{\sqrt{2.62572412}} = 0.19$$

t cal= 0.19

The number of degrees of freedom is N-1

i. e. 10-9 with significant level of 0.05 or 5% gives 2.262.

The null hypothesis is given below:

There is no significant difference between Marketing and Accounting Scores of the Management Sciences students.

$t_{cal} = 0.19$

$t_{tab} = 2.262$

2.2.2 Decision

Since t-calculated value is less than the table or critical value, we accept the Null hypothesis, upholding that there is no significant difference in student's performance in Marketing and Accounting courses.

2.3 The z-test (t-test for Large Independent Groups; Sample > 30)

The z-test is a parametric test which normally and randomly measures how far apart two means are from their standard deviation. Therefore, when the population sizes of the two groups are more than 30, the Z-test is used with the table of the normal curve instead oft-table.

The statistical scale of measurement is Interval scale.

2.3.1 Assumptions the sample size is large and usually more than 30

- the data are at least interval scaled
- the population values are normally distributed

The formula of the z-test large sample independent groups is

$$Z = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{SD_1^2}{n_1} + \frac{SD_2^2}{n_2}}}$$

Where $\bar{X}$ = Mean of group 1

$\bar{X}_2$ = Mean of group 2

SD_1 = Standard Deviation of group 1

SD_2 = Standard Deviation of group 2

n_1 = Number of students in group 1

n_2 = Number of students in group 2

For example, in a related problem and hypothesis as stated before, let $\bar{X}_1$ = 60; $\bar{X}_2$ = 65, SD_1 = 6.5; SD_2 = 5.8; n_1 = 31; n_2 = 31.

$$Z = \frac{60 - 65}{\sqrt{\frac{6.5^2}{31} + \frac{5.8^2}{31}}} = \frac{-5}{\sqrt{\frac{42.25}{31} + \frac{33.64}{31}}}$$

$$Z = \frac{5}{\sqrt{1.36290 + 1.08516}} = \frac{5}{\sqrt{2.44806}}$$

$$Z = \frac{5}{\sqrt{1.5642775}} = \frac{5}{\sqrt{1.25085}} = 3.9972$$

= 3.9972 = 3.99(3s*f*)

2.3.2 Decision

The Z score of -1.96 or 1.96 taken at each end of the normal curve (distribution) cuts off half of five percent of the areas. Similarly, Z score of 2.58 cuts off half of one percent of the data, that is H: $X_1 = X_2$, so when Z_{cal} is 3.99, the Z table at 0.05 level of significance falls between 1.96 and -1.96. Therefore, since $Z_{cal} > Z_{tab}$, we reject the null hypothesis at 5% significant level. While at 0.01 or 1% Z_{tab} is between -2.58 and 2.58, which implies that $Z_{cal} <$ the table.

Therefore, in such situation, we accept the null hypothesis at 1% level of significance.

2.4 The Pearson's Product Moment Correlation and Scales of Data Measurement Usage

In some cases, in statistical scales of data measurement and analysis, we may want to evaluate the direction and degree of relationship (correlation) between the scores in two distributions. For this purpose, we must use a measure of association. The Pearson Product Moment Correlation Coefficient is one of such. The Pearson Product Moment is the most widely used measure of association. It can be used when our dependent measures are scaled on an interval or a ratio scale (Bordens and Abbott, 2002). The Pearson Correlation Coefficient provides an index of direction and magnitude of the relationship between two sets of scores. The Pearson Correlation Coefficient is used when both of the variables are measured along a continuous scale.

The value of the Pearson (r) can range from +1 through zero to -1. The sign of the coefficient tells us the direction of the relationship. A positive correlation indicates a direct relationship (as the values of the scores in one distribution increases, so do the values in the second). A negative correlation indicates an inverse relationship (as the value of one score increases, the value of the second decreases).

The magnitude of the correlation coefficient tells us the degree of linear relationship (straight line) between our two variables. A correlation of zero indicates that no relationship exists. As the strength of the relationship increases, the value of the correlation coefficient increases, toward either +1 or -1. Both +1 and -1 indicate a perfect linear relationship. The sign is unrelated to the magnitude of the relationship and simply indicates the direction of the relationship.

2.4.1 Factors that Affect the Pearson's Correlation Coefficient (r)

As expressed by Bordens and Abbott (2002), before we use the Pearson's Correlation Coefficient, it is necessary for us to examine our data much as we do when deciding on a measure of center. Several factors according to them affect the magnitude and sign of the Pearson correlation coefficient.

- Firstly, one factor that affects the Pearson Correlation Coefficient is the presence of outliers. An outlier can drastically change our correlation coefficient and affect the magnitude of our correlation, its sign or both. This is especially true if the correlation coefficient is based on a small number of pairs of scores.
- Restricting the range over which the variables vary can also affect Pearson *r*.

- The Pearson correlation coefficient is sensitive not only to the range of scores but also to the shapes of the score distributions. It is to be noted that the formula used to calculate the coefficient uses the standard deviation. If the scores are not normally distributed, the mean does not represent the distribution well. Consequently, the standard deviation will not accurately reflect the variability of the distributions, and the correlation coefficient will not provide an accurate index of the relationship between the two sets of scores. Hence, it is necessary to inspect the frequency distributions of each set of scores to ensure that they are normal (or nearly normal) before using the Pearson Coefficient.

- Finally, the Pearson coefficient reflects the degree to which the relationship between two variables is linear.

2.5. The Spearman's Rank Order Correlation Coefficient and scale of Data Measurement Usage

The Spearman Rank Order Correlation is statistically designated as, rho or p or rs. It is used either when the data are scaled on an ordinal scale or when we want to determine whether the relationship between variables is monotonic (Gravetter and Wallnau, 2000). It ranks paired observations, thus requiring at least ordinal data (Baridam, 1990). It measures the degree of relationship between two sets of ranked observations. In order words, Baridam expressed that, it indicates the degree of effectiveness in predicting one ranked variable based on another ranked variable. Rho (symbolized also by rs or p) can assume any value from -1 to +1, indicating perfect correlation, and zero (0) indicates no relationship. The rank order correlation is relatively easy to calculate and can be interpreted in much the same way as a Pearson correlation (Bordens and Abbott, 2002). The formula for the rank order correlation coefficient is:

$$rs = 1 - \frac{6\sum d^2}{N^3 - N} \quad or \quad rs = 1 - \frac{6\sum d^2}{N(N^2 - 1)}$$

Where $\sum d^2$ = sum of' the squared differences in the ranking of the subject on the two variables.

N = number of subjects being ranked.

Example 1: For purposes of illustration in those in elected political office, if we assume that a member of a state house of assembly indicates the interest of determining whether or not a significant relationship exists between the number of money some members of State Assembly in selected Nigerian States may want to spend on hosting birthday party and the amount they may at present time expect to spend on a birthday gift (Baridam, 1990). To statistically examine if an association or relationship exists between the two variables, the Spearman's rank order correlation technique may be used, provided, the data resulting from the variables are measured in ordinal scale and the statistical procedure followed.

To make use of or adopt the procedure, it is necessary to first of all, compute the measure, making use of the data in the Table 3below. This could be obtained using the following five steps (Baridam 1990):

- The n values of X will be replaced by their ranks Rx by designating the rank of i to the "smallest" X and the rank of ii to the 'largest". If two or more X values are tied, they will each be assigned the average rank of the positions they otherwise would have assigned individually if the ties did not occur.

- The n values of Y should be replaced by their ranks Ry as applicable in step 1

- In each of the n items, obtain a set rank difference scores, di = Rxi Ryi. Where, i= 1, 2,…..N

- Obtain the summation of squared rank difference scores,
- The Spearman Rank Order Correlation Coefficient (rs or rho or p) is as given by the formula already stated above.

Table 3: Determining Spearman's of Rank Correlation Coefficient

Assembly Member	Amount Spent on Birthday Gift		Amount Spend on Hosting Birthday Party		D	d^2
	Naira X	Rank Rx	Naira Y	Rank R_y		
1	35	6.5	200	2	4.5	20.25
2	45	8.5	500	9.5	-1	1
3	35	6.5	400	6.5	0	0
4	30	5	450	8	-3	9
5	50	11	400	6.5	4.5	20.25
6	45	8.5	150	1	7.5	56.28
7	20	1.5	250	3	-1.5	2.25
8	20	1.5	300	4	-2.5	6.25
9	48	10	350	5	5	25
10	60	12	550	11	1	1
11	65	13	500	9.5	3.5	12.25
12	25	3.5	600	12	-8.5	72.25
13	35	6.5	13	5	-9.5	90.25
				Total	**∑d= 0***	**316**

*Sum of deviations must equal 0

Source: Baridam, D. M. (1990). *Research Methods in Administrative Sciences,* Port Harcourt: BELK publishers (with modifications)

From the data in Table 3 above, the analyst can proceed to compute the Spearman's rank correlation (rs), since the objective of the researcher (study) is to determine the existence of the correlation the test is two-tailed. For a two-tailed test, the null and alternative hypotheses as relatedly specified by Baridam (1990) are:

Ho: There is no significant relationship between the amount of money spent on the hosting a birthday party and the amount spent on birthday gift.

H_A: There is a significant relationship between the amount of money spent on the hosting a birthday party and the amount spent on birthday gift.

From the formula,

$$\text{rs} = 1 - \frac{6\,x\,316}{13^3 - 13} = 1 - \frac{1896}{2184} = 0.13$$

The rs of 0.13 shows a weak association or correlation between the test variables.

For the purpose of testing the null hypothesis, we have

$$Z = \text{rs}\ \sqrt{n-1} = 0.13\sqrt{12} = 0.45$$

0.05 significant level,

For a two-tailed test with a 0.05 significant level, the conventional critical Z values are ±1.96. Since Z = 0.45 falls between these critical values, the null hypothesis is, therefore, accepted.

Thus, the researcher may conclude that there is no significant association between the amount of money spent on hosting a birthday party and the amount spent on the birthday gift.

2.6. The Simple Regressional Analysis and Scale of Measurement Usage

The simple linear regression and prediction is a topic closely related to correlation. It is of a parametric test technique analysis. Its scale of data measurement is on INTERVAL SCALE. It is to be recalled that with simple correlational technique, one can establish the direction and degree of relationship between two variables; while with this simple linear regression, we can estimate values of a variable based on knowledge of the values of others (Bordens and Abbott, 2002).

2.6.1 Bivariate Regression

The idea behind bivariate linear regression is to find the straight line that best fits the data plotted on a scatterplot.

Table 4: Data for Linear Regression Example

X	Y	$\left(X_j - \bar{X}_j\right)$	$\left(Y_j - \bar{Y}_j\right)$	$\left(X_j - \bar{X}_j\right)\left(Y_j - \bar{Y}_j\right)$	$\left(Y_j - Y_j\right)^2$
7	8	1.40	1.30	1.82	1.96
3	4	-2.60	-2.70	7.02	6.76
2	4	-3.60	-2.70	9.72	12.96
10	9	4.40	2.30	10.12	19.36
8	9	2.40	2.30	5.52	5.76
7	7	1.40	0.30	0.42	1.96
9	8	3.40	1.30	4.42	11.56
6	8	0.40	1.30	0.52	0.16
3	4	-2.60	-2.70	7.02	6.76
1	6	-4.60	-0.70	3.22	21.16
X-5.6	**Y=6.7**			**SP = 49.80**	**SSx = 88.4**

If we consider an example of a hypothetical production management example using the data presented in the table above, which shows the scores of each of 10 production centers or units on two measures (X and Y), The scatter plot of these data is as shown below.

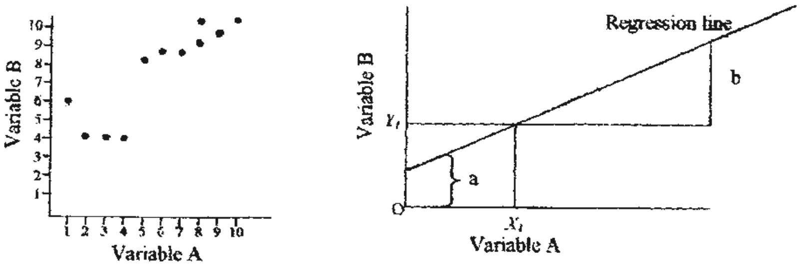

Figure 1: Scatter plot of Data from Table 4 above and the Regression Line

By the application of the linear regression analysis, we want to find the straight line that best describes the linear relationship between X and Y. The best fitting straight line is the one that minimizes the sum of the squared distances between each data point and the line, as measured along the Y-axis (least squares criterion). This line is called the least squared regression line. At any given value of X found in the data, the position of the line indicates the value of Y predicted by the linear relationship between X and Y. We can then compare these values predicted from the linear relationship between X and Y. We can as well compare these predicted values with the values actually obtained. The best

fitting straight line minimizes the difference between the predicted and obtained value.

The regression line is described mathematically by the following formula:

$$\hat{Y} = a + bx$$

Where $\hat{Y}$ is the predicted Y score;

b is the slope of the regression line (also called regression weight);

x is the value of the x-variable, and;

a is the Y-intercept (Pagano, 1994; in Bordens and Abbott, 2002)

The constants, a and b, define a particular regression line. We can use the following formula to determine the value of b for a given set of data points (Gravetter and Wallnau, 2000).

$$b = \frac{SP}{SSx}$$

Where SP = $(X - \overline{X})(Y - \overline{Y})$

SS = $\sum (X - \overline{X})^2$

Using the numbers in table 4 above, we have

$$b = \frac{49.5}{88.4} = 0.56$$

The formula for the Y intercept (a) is

$$a = \overline{Y} - b(\overline{X})^2$$

For example,

a = 7 – 0.56(5.6) = 3.6

Substituting these values for b and a in the regression equation gives

$\hat{Y}$ = 0.56X + 3.56

This equation allows us to predict the value of Y for any given value of X. For example,

If X=6, then $\hat{Y}$ =0.56(6) + 3.56 = 6.92

2.7. The Analysis of Variance (ANOVA) and Scale of Measurement Usage

The scale of measurement used in ANOVA is interval or ratio scale. When our study or experiment includes more than two groups, the statistical test of choice is an analysis of variance (ANOVA). As the name implies, ANOVA is based on the concept of analyzing the variance that appears in the data. For this analysis, the variation in scores is divided, or partitioned, according to the factors assumed to be responsible for producing that variation.

These factors are referred to as sources of variance. The next section describes how variation is partitioned into the source and how the resulting source variations are used to calculate a statistic called F-ratio. The F-ratio is ultimately checked to determine whether the variation among means is statistically significant.

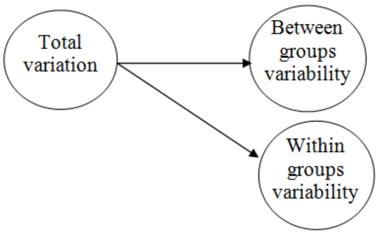

Figure 2: Partitioning total Variation into between – Groups and within Groups Source

Source: Adapted from Bordens, K. S. and Abbott, B. B. (2002). *Research Design and Methods: A Process Approach*, New York: McGraw-Hill High Education Company.

The ANOVA is used to compare three or more groups' means on the following conditions.

- The items in the different groups must be selected by random sampling from normal distribution and
- The group must not be dependent on any other ones (Osaat and Nwanna-Nzewunwa, 2002).

There are two basic types of ANOVA viz: One-way ANOVA and two-way ANOVA. For purposes of brevity, only a one-way ANOVA example is appealed to be considered in this present study.

2.7.1 One-way ANOVA

The items usually considered are:

- Total sums of squares (SS Total)
- Between sum of squares (SS Between)
- Within sum of squares (SS Within)
- The final result of ANOVA (called F-ratio)

2.7.1.1 Example:

We shall consider three production management centers or units groups with means $\overline{X}_1, \overline{X}_2$ *and* $\overline{X}_3$

The hypothesis to be tested is stated thus:

Ho: There is no significant difference between the three groups mean i. e.

$$\overline{X}_1 = \overline{X}_2 = \overline{X}_3$$

Table 5: Below shows the Calculation of One-Way ANOVA

	Group I		Group 2		Group 3	
	X1	X_1^2	**X2**	X_2^2	**X3**	X_3^2
1	7	49	9	81	4	16
2	6	36	7	49	5	25
3	8	64	3	9	7	49
4	9	81	4	16	8	64
5	10	100	5	25	9	81
6	5	25	5	25	7	49
7	4	16	6	36	6	36
8	3	9	8	64	5	25
9	8	64	4	16	9	81
10	2	4	5	25	3	9
	$\sum X1 = 62$	$\sum X_1^2 = 448$	$\sum X2 = 56$	$\sum X_2^2 = 346$	$\sum X3 = 63$	$\sum X_3^2 = 435$

$\overline{X}_1 = 6.2;\ \overline{X}_2 = 5.6;\ \overline{X}_3\ 6.3$

But $\sum X_1 = 62$; $\sum X_2 = 56$; $\sum X_3 = 63$; $\sum X = 181$

$\sum X_1^2 = 448$; $\sum X_2^2 = 346$; $\sum X_3^2 = 435$

$\therefore \sum X^2 = 448 + 364 + 435 = 1229$

N = 10 + 10 + 10 = 30

The calculation of groups items

(a) $SS_{total} = \sum X^2 - \frac{\left(\sum X\right)^2}{N} = 1229 - \frac{(181)^2}{30}$

$\Rightarrow$ 1229 – 1092.03 = 136.97

(b) $SS_{between} = \frac{\left(\sum X_1\right)^2}{N} + \frac{\left(\sum X_2\right)^2}{N} + \frac{\left(\sum X_2\right)^2}{N} - \frac{\left(\sum X\right)^2}{N}$

$$\Rightarrow \frac{(62)^2}{10} + \frac{(56)^2}{10} + \frac{(63)^2}{10} - \frac{(181)^2}{10}$$

$\Rightarrow$ 384.4 + 313.6 + 396.9 – 1092.03 = 287

(c) $SS_{within} = SS_{total} - SS_{between}$

= 136.97 – 2.87 = 134.1

(d) The F-Ratio = $\frac{SS_{between} / df_{between}}{SS_{within} / df_{within}}$

NB: d/f between = K – 1, where K is no of groups

d/f within = N – K

d/f total = N – 1

i. e. df between = 3 – 1 = 2

df within = 30 – 3 = 27

df total = 30 – 1 = 29

The F-Ratio = $= \frac{2.87/2}{134.1/27} = \frac{1.44}{4.97} = 0.29$

∴ F-ratio = 0.29

The result can be summarized thus:

Table 6: Summary of the ANOVA Results

Source of Variation	Sum of Squares	df	Mean Square	F-Ratio	Level of Significance
Between Group	2.87	2	1.44	0.29	0.05
Within Group	134.1	27	4.97		
Total	**136.97**	**29**			

F-Ratio table value with 27 and 2 degrees of freedom at 0.05 level of significance is 3.35.

2.7.2 Decision

Since calculated F-Ratio value (0.29) is les than the table F-Ratio value (3.35), we accept the Null Hypothesis that there is no significant difference among the measures of the three groups and reject the alternative hypothesis.

3. CONCLUSIONS

The study has examined the basic data measurement, scales and their respective statistical techniques test relevance in contemporary business management research. It is to be noted that most often, some researchers select a particular statistical test not because such a test is appropriate for their data, but because it is the only statistical test they can manipulate. Invalid conclusions often arise whenever a wrong scale of data measurement and statistical test tools or techniques are used in analyzing the data. When this happens, wrong statistical and management decisions are arrived at and the purpose of the study is defeated.

RECOMMENDATIONS

In view of getting accurate statistical decisions, it is therefore recommended that the nature of the data (i. e. nominal, ordinal, interval and ratio), the hypothesis and their analytical/ statistical techniques procedure should of necessity, be taken into consideration when selecting a statistical test. Care should be taken in the choice of data measurement scale and relevance to the specific study in question.

REFERENCES

1. *Baridam, D. M. (1990). Research Methods in Administrative Sciences, Port Harcourt; BELK Publishers.*
2. *Bordens, K. S. and Abbott, B. B. (2002). Research Design and Methods: A Process Approach, New York: McGraw-Hill Higher Education Company.*
3. *Cohen, L.; Manion, L. and Morrison K. (2007). Research Methods in Education, New York: Routlege Publishers.*
4. *Dana, S. D. (2001). Statistics and Data Analysis for the Behavioural Science, New York: McGraw-Hill Co.*
5. *Gravetter, F. D. and Wallnau, LB. (2002). Statistics for the Behavioural Sciences (5th ed.) St. Paul; MN West Pub.*
6. *Kerlinger, F. (1973). Foundations of Behavioural Research, 2nd ed. New York: Holt Rinehart.*
7. *Osaat, S. D. and Nwanna-Nzewunwa (2002). Fundamentals of Educational Research, Oghelli, DeltaState: Eddy-Joe Publishers.*
8. *Osuala, E. C. (1982). Introduction to Research Methodology, New York: Exposition Press.*
9. *Pagano, R. R. (1998). Understanding Statistics in the Behavioural Sciences. St. Paul: MN West.*
10. *Roscor, J. T. (1975). Fundamental Statistical for the Behavioural Sciences, 2nd ed, New York: Hott, Rinehart and Winston.*
11. *Selltiz, C.; Wrightsman, L. S.; and Cook, S. W. (1976). Research Methods in Social Relations, 3rd ed. New York: Holt, Rinehart and Winston.*
12. *Siegel, S. and Castellan, N. J. (1988). Nonparametric Statistics for the Behavioural Sciences, 2nd ed., New York: McGraw-Hill.*
13. *Smith, H. W. (2004). Methodological Issues in No-Experimental Research, London: Open University Press.*
14. *Stevens, S. (1971). "Scales of Measurement", In J. A. Steger, Readings in Statistics for the Behavioural Scientists. New York: Holt and Winston.*
15. *Stone, E. F. (1978). Research Methods in Organizational Behaviour, Santa Monica, California: Good Year Publishing Company Inc.*